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The relationship among natural gas energy consumption, capital and economic growth: Bootstrap-corrected causality tests from G-7 countries

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This paper examines the relationship between natural gas consumption, economic growth and capital by using G-7 countries data and a bootstrap-corrected causality test for the period 1970–2008. It was found eight significant Granger causality relationships. For Italy, the Granger causality is from natural gas consumption to growth and United Kingdom adverse. For pattern of France, Germany and United States there is two sided Granger causality between natural gas and growth.

Contents

1. Introduction

Economic growth and energy consumption relationship has been extensively examined in the energy economics literature. Following Kraft and Kraft [1]'s study which is the first of energy economics literature, examined the energy use and economic growth relationship in the USA, researchers study on the relationship between energy consumption and GDP (GNP), using different period, data and econometric methods on different countries. But the results of these studies are mixed and ambiguous (see Ozturk [2], Payne [3], [4]), Reynolds and Kolodziej [5] found unidirectional causality, Soytas and Sari [6] found bidirectional causality and Ozturk and Acaravci [7] found no causality.

The relationship of Energy consumption (EC) and GDP is vital because of three different aspects, economic growth, scarcity and environment pollution for policy makers. If there is a strong relationship between EC and GDP, it is very hard to make energy conservation or friendly environment policies for policy makers. In energy economics literature, the causality relationship between GDP and EC can be categorized in four types (see Fallahi [8]); *Conservation hypothesis* is valid, if there is causality from GDP to EC, that suggests energy conservation will not negative effect on the GDP, but if the causality is from EC to GDP, *Growth hypothesis* is valid and emphasize that EC reduction would decrease the GDP. *Feedback hypothesis* suggests bidirectional causality between EC and GDP; the last hypothesis is *Neutrality hypothesis* and says EC and GDP relationship is not significant.

Energy economics literature is quite substantial on EC and GDP relationship studies. But it must be separated on energy sectors, especially developing countries use coal more than natural gas and developed countries adverse, so the recent interest in energy economics literature separately must be on electricity consumption, coal consumption, natural gas consumption and the other energy sectors.

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Table 1
Energy consumption, natural gas consumption and economic growth relationship empirical literature.

Author(s)	Countries	Methods	Variables	Conclusion(s)
Yu and Choi [23]	USA(1947–1979) UK (1950–1976)	Sims and Granger causality	EC; real GNP	USA; Neutrality hypothesis UK; Growth hypothesis
Murray and Nan [24]	Canada, France, Germany, UK, USA (1970–1990)	Granger causality	EC; ELC; real GDP	Canada; Growth hypothesis France, Germany, UK, USA; Neutrality hypothesis
Soytas and Sari [25]	Canada, France, Germany, Japan, UK, USA (1950–1992), Italy (1953–1991)	Johansen-Juselius; VDC	EC; GDP per capita	Canada, UK, USA; Neutrality hypothesis France, Germany, Japan; Growth Hypothesis Italy; Conversation hypothesis
Soytas and Sari [6]	Canada, Italy, Japan, UK, USA (1960–2004), France (1970–2002), Germany (1971–2002)	Johansen-Juselius; VDC	EU; real GDP per capita; LF; CF	Canada, Germany, Italy, Japan and UK; Feedback hypothesis France and USA; Conservation hypothesis
Narayan and Smyth [26]	G 7 Countries (1972–2002)	Panel Unit Root, Panel cointegration, Granger Causality and long run estimation	CF; EC; real GDP	CF, EC, GDP cointegrated, CF and EC Granger cause GDP in long run
Reynolds and Kolodziej [5]	Former Soviet Union (1987–1996)	Granger causality	OP; CP; NGP; GDP	OP; Conversation hypothesis, CP and NGP; Growth hypothesis
Ozturk and Acaravci [7]	Turkey (1968–2005)	ARDL, error-correction based Granger causality models	EC; GDP; CE	Neutrality hypothesis
Lee and Chien [27]	G 7 Countries (1960–2001)	Toda-Yamamoto, Granger Causality test	EC; real GDP per capita	Canada, Italy and UK; Growth hypothesis Japan and France; conservation hypothesis Germany and USA; Neutrality hypothesis
Apergis and Payne [9]	67 countries (1992–2005)	Panel cointegration test, panel error correction model	NGC; real GDP; CF; LF	Long-run equilibrium relationship between GDP, NGC, CF, LF, Short-long run bidirectional causality between NGC and GDP
Payne [10]	USA (1949–2006)	Toda-Yamamoto long-run causality	NGC; real GDP	Conversation hypothesis
Apergis and Payne [28]	Central America Countries (1980–2006)	Panel error correction model	REC; real GDP	Feedback hypothesis
Lim and Yoo [29]	Korea (1991–2008)	Granger causality	NGC; real GDP	Feedback hypothesis

Note: Energy Usage (EU), Energy Consumption (EC), Renewable Energy Consumption (REC), Natural Gas Consumption (NGC), Coal Consumption (CC), Electricity Consumption (ELC), Oil consumption (OC), Industrial Energy Consumption (IEC), Real GDP (GDP), Capital Formation (CF), Labor Force (LF), Oil Production (OP), Coal Production (CP), Natural Gas Production (NGP), Carbon Emissions (CE).

This study focuses on the relationship between economic growth and natural gas consumption in G-7 countries, because natural gas consumption-economic growth nexus literature is rather limited. Reynolds and Kolodziej [5] used Granger causality to test natural gas, oil, coal production and GDP relationship in the former Soviet Union and find support for oil, coal and natural gas production, the conversation hypothesis and the growth hypothesis, respectively. Apergis and Payne [9] employed panel cointegration test and panel error correction model to test National Gas Consumption (NGC); real GDP; Capital Formation (CF) and Labor Force (LF) relationship for 67 countries and find long-run equilibrium relationship between GDP, NGC, CF, LF, short-long run bidirectional causality between NGC and GDP. Payne [10] used Toda-Yamamoto long-run causality test to NGC and real GDP relationship, find support for conversation hypothesis in the cases of USA.

A few and mainly study of the empirical literature on the causal relationship between energy consumption, natural gas consumption and economic growth are presented at Table 1.

Natural gas is a key non-renewable energy source for the industrial sector and electricity generation for a majority of countries around the world. And it is more efficient and less carbon-intensive than other fossil fuels (see IEO [11]). World natural gas consumption increases by 52 percent in the reference case. Natural gas continues to be the fuel of choice for many regions of the world in the electric power and industrial sectors. In the power sector, low capital costs and fuel efficiency also in favor of natural gas (see IEO [12]).

The magnitude of the natural gas consumption between the G 7 countries is summarized in Table 2. United States is the largest consumer and consume up the total consumption in other countries

Table 2
G 7 countries natural gas consumption.[a]

	2000	2004	2008
Canada	2,485,397	2,445,990	2,462,989
France	1,495,483	1,603,608	1,537,766
Germany	2,563,827	2,838,095	2,735,403
Italy	1,795,133	1,919,116	1,736,177
Japan	1,074,772	1,249,690	1,517,314
United Kingdom	2,439,273	2,425,896	2,198,021
United States	16,746,652	15,538,781	15,246,552

Data source: IEA 2010.
[a] (Billion cubic feet)

Table 3
Lag selection.

Selection	Countries						
	Canada	France	Germany	Italy	Japan	United Kingdom	United States
Var order	(1)–[1]	(2)–[2]	(2)–[3]	(1)–[1]	(1)–[1]	(1)–[1]	(4)–[4]
Lag order	(1)–[1]	(2)–[2]	(2)–[3]	(1)–[1]	(1)–[1]	(1)–[1]	(4)–[4]

Note: In parenthesis order value is illustrated for NGC to GDP relations, and in brackets order value is illustrated for GDP to NGC relations by employing Hatemi J Criteria (HJC).

almost 2 times. Japan is the fewer user in G-7 countries all period but only country from 2004 to 2008 consumption value increased, the others decreased. In this case, according to the consumption values, United States may be stand alone group, Canada, Germany and United Kingdom triple group, France, Italy and Japan are the other triple group. The rest of the paper is organized as follows: The next section describes the data, methodology and the results from empirical analysis. Section 3 presents conclusion and policy implications of the paper.

2. Data, methodology and results

The source of Gross Domestic Product (GDP) and Gross Fixed Capital Formation variables for G 7 countries due to availability of data[1] is from OECD National Accounts data that is attained from source OECD data base and final energy consumption data is obtained from International Energy Agency (IEA) database. In the analysis, to ensure robustness for the common components of natural gas consumption, GDP and capital, several unit root tests are employed[2], including the augmented Dickey and Fuller [13] (ADF) test and Phillips and Perron [14] (PP) test. According to our results, the common components of natural gas consumption, GDP and capital all turn out to be integrated of order one, I(1).

The next step is to pick optimal lag order[3]. Two of the most successful criteria according to the simulation results presented in the literature are Schwarz [15] Bayesian information criterion and the Hannan and Quinn [16] information criterion. However, the earlier studies illustrate that each of these two different criteria can perform better than the other depending on the properties of the true VAR model. Hatemi-J Criteria (HJC), displayed in Table 3, is employed to pick true lag order which is suggested by Hatemi-J [17].

Causality relationships between growth and energy are frequently analyzed using Granger causality test. Granger [18] runs a regression model which relies on asymptotic distribution theory. But, using Monte Carlo simulations Granger and Newbold [19] find that if the variables are non-stationary, the regression analysis based on the asymptotic distribution theory does not work well. So the found results can be spurious. Sims et al. [20] depicted that when the variables are non-stationary the vector autoregressive (VAR) model cannot be used in level form even if the variables are co-integrated due to useless of asymptotic distribution theory. Based on lag augmented VAR model, Toda and Yamamoto [21] suggest a Wald test statistic that asymptotically has a chi-square distribution irrespective of the order of integration or co-integration properties of the variables in the model. Toda and Yamamoto [21] suggest the following augmented VAR $(p+d)$ model:

$$x_t = \nu + A_1 x_{t-1} + \cdots + A_p x_{t-p} + \cdots + A_{p+d} x_{t-p-d} + \varepsilon_t. \quad (1)$$

[1] France (1960–2008), Canada, Germany, Italy, Japan, United Kingdom and United States (1970–2008).

[2] The unit root test results are available upon request from the authors.

[3] The multivariate ARCH effects and normality are also analyzed.

It is assumed that the order p of the process is known and d is equal to the maximum order of integration of the variables. Toda-Yamamoto augmented VAR$(p+d)$ model can be described in the following a compact way:

$$K = FZ + \psi. \quad (2)$$

where

$$K = (x_1, \ldots, x_T)(n \times T) \quad \text{matrix},$$

$$F = (\nu, A_1, \ldots, A_p, \ldots, A_{p+d})(n \times (1 + n(p+d))) \quad \text{matrix},$$

$$Z_t = \begin{bmatrix} 1 \\ x_t \\ x_{t-1} \\ . \\ . \\ . \\ x_{t-p-d+1} \end{bmatrix} ((1 + n(p+d)) \times 1)\,\text{matrix}, \quad \text{for}\ t = 1, \ldots, T,$$

matrix,

$$Z = (Z_0, \ldots, Z_{T-1})((1 + n(p+d)) \times T) \quad \text{matrix},$$

$$\psi = (\varepsilon_1, \ldots, \varepsilon_T)(n \times T) \quad \text{matrix},$$

Toda and Yamamoto [21] introduce the following modified Wald (MWALD) test statistic for testing the null hypothesis of non-Granger causality:

$$\text{MWALD} = (Y\phi)'[Y((Z'Z)^{-1} \otimes V_U)Y']^{-1}(Y\phi) \sim \chi^2_P. \quad (3)$$

where $\otimes$ = the Kronecker Product; V_U = the estimated variance – covariance matrix of resdiuals in Eq. (2) when the null hypothesis of non-Granger causality is not imposed.; $\phi = vec(F)$, where vec represents the column stacking operator.

The MWALD test statistic is asymptotically χ^2 distributed, conditional on the assumption that the error terms are normally distributed, with the number of degrees of freedom equal to the number of restrictions to be tested. According to Toda and Yamamoto [21], their function (Eq. (2)) guarantees the use of asymptotical distribution theory. However, using Monte Carlo simulations Hacker and Hatemi-J [22] showed that the MWALD test statistic over rejects the null hypothesis, especially if the error term is characterized by autoregressive conditional heteroscedasticity (ARCH) and non-normality. Furthermore Hacker and Hatemi-J urged that the asymptotic distribution can be a poor approximation, especially for the small samples that are common in empirical studies.

Hacker and Hatemi-J [22] found that the bootstrapped empirical size for the modified Wald test is close to the correct size in the different cases when the extra lags are greater than or equal to the integration order of both variables, and it is generally closer to the correct size than the asymptotic distribution empirical size.

To perform the bootstrap simulations, firstly regression (Eq. (2)) is estimated with the null hypothesis of no Granger causality. For each bootstrap simulation it is generated the simulated data, K^*.

$$K^* = \hat{F}Z + \psi^* \quad (4)$$

Table 4
Bootstrap-corrected causality test.

Countries	Natural gas does not Granger cause growth				Growth does not Granger cause natural gas			
	MVALD	%1 CV	%5 CV	%10 CV	MVALD	%1 CV	%5 CV	%10 CV
Canada	0.131	7.642	4.118	2.823	1.816	7.668	4.142	2.906
France	46.144***	10.765	6.408	4.851	81.053***	12.577	7.031	4.949
Germany	15.704***	10.709	6.656	4.836	10.456**	14.264	9.004	6.968
Italy	4.312**	7.604	4.090	2.87	0.314	7.269	4.174	2.919
Japan	0.224	8.450	4.662	3.262	1.046	8.383	4.259	2.980
United Kingdom	0.422	7.635	4.252	2.965	3.989*	7.849	4.283	2.924
United States	15.399**	19.054	12.128	9.295	10.934*	18.023	11.691	9.104

Note:
* Significance at the 10% significance level, based on bootstrap critical values.
** Significance at the 5 significance level, based on bootstrap critical values.
*** Significance at the 1% significance level, based on bootstrap critical values.

where $\hat{F}$ is the estimated value of the parameters in Eq. (2). That is the $\hat{F} = KZ'(ZZ')^{-1}$ bootstrap residuals (Ψ^*) are based on T random draws with replacement from the regression's modified residuals, each with equal probability of $1/T$. The mean of the resulting set of drawn modified residuals is subtracted from each of the modified residuals in that set. The modified residuals are the regression's raw residuals modified to have constant variance, through the use of leverages. Eq. (5) defines the modified residual through leverage adjustment for x_{it}.

$$\varepsilon_{it}^{m} = \frac{\varepsilon_{it}}{\sqrt{1-h_{it}}} \tag{5}$$

here hit is the *tth* element of *hi* and ε_{it} is the raw residual from the regression x_{it} (i = 1,2,3,4). $T \times 1$ leverages vectors for $x1t$ and x_{jt} are respectively defined as:where $X = (K'_{-1}, \ldots, K'_{-p})$ and $X_i = (K'_{i,-1}, \ldots, K'_{i,-p})$. For the equation that determines x_{1t}, X_1 is the explanatory variable matrix. This equation is restricted to have no Granger causality. For the equation that determines x_{jt}, X is the explanatory variable matrix. This equation permits all lags of all variables to be included. This is the case when the null hypothesis that x_{jt} does not Granger cause x_{1t} is tested. If the null hypothesis imposes that x_{1t} does not Granger cause x_{jt}, a corresponding procedure can be conducted. In order to calculate the bootstrap critical values, the bootstrap simulation is run 100,000 times and calculated the MWALD test statistic each time. In this way, it helps to produce the empirical distribution for the MWALD test statistic.

Table 4 indicates bootstrap-corrected causality test results. MVALD statistic values were compared to %1, %5 and %10 bootstrap critical values. According to results, it was found eight significant Granger causality relationships in Table 4. For Italy the Granger causality is from natural gas consumption to growth and United Kingdom adverse. For pattern of France, Germany and United States there is two sided Granger causality between natural gas and growth.

3. Conclusion

Previous studies of the relationship between natural gas consumption, economic growth and capital in G 7 countries have found ambiguous results. This study examines natural gas consumption, economic growth and capital nexus by using an alternative methodology based on the leveraged bootstrapped simulation techniques using data from G 7 countries. From the tests results while there exists uni-directional causality running from energy to GDP in Italy and adverse in United Kingdom. Bidirectional causality is found for France, Germany and United States. Moreover the findings in case of the United Kingdom support the conservation hypothesis, pattern of Italy is in favor of the growth hypothesis and France, Germany and United States support the feedback hypothesis. In the cases of Canada and Japan's findings are favors of the neutrality hypothesis.

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